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Research Article

A Mixed Equilibrium Model and Optimal Path Platooning Method for CAV Platoons in Heterogeneous Traffic Flow

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As the emergence of the connected and autonomous vehicles (CAVs), the platooning technology is believed to play a key role in the future intelligent transportation system. However, current studies mainly focus on the beneficial sides of CAV platoons, and less attention is given to their negative effects. This study develops a mixed equilibrium model for CAV platoons and human-driven vehicles (HDVs), which consider both the positive and negative sides of CAV platooning. On the positive side, CAV platoons are assumed to follow user equilibrium (UE) route choice for their information advantages, while HDVs to follow stochastic user equilibrium (SUE). CAV platoons are also presumed to improve the road capacity. On the negative side, the speed of CAV platoons is slower than that of HDVs for safety stakes, which will impede the latter to overtake. The HDVs is split up into overtaking and nonovertaking flows with different speeds. Furthermore, the model is built up as a mixed UE-SUE equilibrium problem and reformulated as a nonlinear complementarity problem. In addition, an optimal path platooning method is proposed to reduce the negative effects, by integrating travel costs of both CAV platoons and HDVs into its objective function. Numerical results show that the introduction of CAV platoons may increase the travel cost at the initial stage, and the proposed method can effectively reduce the platooning disturbance, thus helps promoting the wider applications of CAV platoons.

1. Introduction

In recent years, the connected and autonomous vehicles (CAVs) have matured rapidly and been put into trial in public roads successfully. Compared with the traditional human-driven vehicles (HDVs), emerging CAVs are equipped with multiple sensors, wireless communication systems, and computing and control units, which effectively improve their vehicle perception range and enhance the information interaction ability in real-time. The wider application of CAVs can potentially improve the road network capacity, traffic efficiency, travel comfort, and safety [1, 2]. Nevertheless, the extent of potential improvement depends not only on the CAV market penetration rate (MPR) but also on appropriate CAV operating mechanisms.

Vehicle platooning stands out among various CAVs technologies for its social benefits to traffic flow. Platooning entails collaboration between the multiple vehicles to achieve stable and close car-following, which will help to improve the efficiency of the transportation system [3]. Thus, the primary benefit of vehicle platooning is the increasing roadway capacity, and the capacity gain is positively correlated with the platoon size [4]. The road capacity value can exceed 12,000 vehicles per hour and lane under the best possible platooning conditions, which is more than 5.3 times the value with no CAVs at all [5]. From the perspective of vehicle dynamics, Huang et al. [6] found that cooperative driving systems with automated vehicle platoons can increase traffic capacity due to better interactions between the vehicles. Chang et al. [7] demonstrated that smaller desired time headway and a larger maximum platoon size are advantageous for the improvement of the mixed flow capacity. Xin et al. [8] indicated that encouraging CAVs to drive in tight-platoons can reduce congestion and improve road capacity at higher traffic demand. In addition, the vehicle platoon technology also has other potential benefits, such as traffic safety, mobility improvements, energy conservation, and decreased pavement fatigue damage [8–12].

Vehicle driving in platoons increases traffic homogeneity, but adverse effects on traffic flow may also appear. First, the complexity of information flow topology will increase because of the dynamic movement of the vehicle platoons [13]. Second, the dynamic combination of different vehicle types may aggravate the traffic oscillations, as the diversity in the mechanical features of vehicles implies problems due to different acceleration and braking rates [14]. Moreover, different automation degrees may further cause varied reaction times and intervehicle space gaps. Third, an improper platoon length could lead to traffic problems. The most common problem in long platoons is the bottleneck effects caused by the increased difficulty for other nonplatooning vehicles to cross or bypass, which blocks the operations of HDVs such as overtaking or changing lanes. Besides, some drivers are used to choose small gap to change the necessary lanes. For instance, even if the truck drives at gaps of 65 mph (about 100 km/h) for 0.6 s, which equates to a gap of 17.5 m, the vehicle is still willing to change lanes and thus cuts through the truck platoon [15]. As a result, if an HDV suddenly comes out, the platoon will easily be interrupted, which will destroy the stability of the platoon and aggravate the traffic oscillations, causing severe collision accidents. Moreover, the collision risk of the platoon has also become a problem that cannot be ignored, such as sudden lane change of free cars in adjacent lanes, obstacles in front of roads and sudden deceleration, and lane change of leading cars. All these speed disturbance changes caused by vehicle braking systems will lead to continuous fluctuation of the platoon speed [16], which will result in collisions, seriously affecting the traffic safety and traffic flow of surrounding road sections. Therefore, reasonable platooning setting and route planning are necessary.

It is expected that the market penetration rate of CAVs will approximate to 75% in 2035 [17], so the common scenario in the near future would be mixed traffic with CAVs and conventional HDVs coexisting [3]. Nevertheless, HDVs have weaker ability to obtain the global road network information, and their behavior is highly heterogeneous and random [18]. The asymmetry of the information interaction between two types of vehicles in mixed traffic flow would aggravate the complexity of traffic flow. Therefore, there is an urgent need to investigate the influence of CAV platoons running under the mixed traffic environment.

Concerning the mixed CAV-HDV traffic, many studies have been conducted from the microlevel, considered both the positive and negative effects of CAV platooning. First, combining the CAV advantages of road cooperative control, Gong and Du [19] developed a novel cooperative platoon control for a mixed flow platoon, in which the cooperative model predictive control determines the movement of CAV platoons optimally, while considering the interference of the HDV platoon located in or between them. However, the experimental results showed that the cooperative platoon control can dampen traffic oscillation propagation and stabilize the traffic flow more efficiently. Based on the fact that CAV can make more effective use of green time resources than HDV. Liu et al. [20] modeled the maximum throughput of intersections under mixed traffic flow conditions and found that CACC strings can drive through the intersection with the advantages of reducing delay and increasing speed. Wu et al. [21] found that high CAV permeability does not necessarily correspond to high intersection capacity, and only when the platooning willingness is controlled within the corresponding range, it can obtain the positive influence of penetration. It is also shown that heterogeneous acceleration and car-following behavior may create persistent voids and diminish traffic throughput [22]. Yang et al. [23] formulated a mixed-integer linear programming problem to optimize the signal timing plan and arrival time of CAVs, and simulation results showed that both mobility and fuel economy benefit from the cooperative driving framework. Thereafter, the exploration of platoon length arrangement has gone deeper. Sala and Soriguera [5] provided a generalized macromodel to estimate the average platoon length in vehicles. Zhou et al. [4] explored the influence of CAV platoon management and control mode degradation based on the fundamental diagram. The sensitivity analysis of platoon size showed that the significant capacity gain from platoon size exhibits a diminishing marginal effect, so the recommended value of platoon size is 5 when the capacity gain reaches maximum efficiency. When taking both road capacity and pollutant emissions into account, the overall optimal size of CAV platoons is between 5 and 10 [1]. Furthermore, Mohajerpoor and Ramezani [24] explicitly considered the arrangement of CAVs and HDVs in the mixed traffic flow, and derived the analysis model for the expected saturation flow and delay of the mixed traffic.

However, from the macrolevel of perspective, the current literature merely focuses on the beneficial aspects of CAV platooning. Mehr and Horowitz showed that CAV platoon deployment will improve the network mobility [25]. Considering that the aggregate lane choice of vehicle platoon also affects the efficiency of the traffic flow, Mehr et al. [26] further provided a game theoretic framework for macroscopically modeling the aggregate lane choice and bypassing behavior of vehicles at traffic diverge. The model not only predicts the fraction of vehicles that perform bypasses at a traffic diverge to take an exit link but also can be used to mathematically find the optimal lane choice of the commanded vehicles for any given autonomous vehicles penetration rate. To achieve the maximum macrocapacity through lane choice, Chen et al. [27] believed that CAVs should use the most efficient lane to the maximum possible extent and then move to the less efficient lanes. As the reasonable platoon organization can effectively improve the throughput, Woo and Skabardonis [2] proposed a flow-aware strategy of platoon organization that forms longer CAV platoons and ensures maximal traffic flow without a capacity drop. On the other hand, with the fact that velocity fluctuations will be eliminated in a fully automated traffic, Vranken et al. [28] introduced a cellular automaton design method to model the different behaviors of the automated and human vehicle, indicating that the traffic capacity in heterogeneous automatic traffic increased. However, with the increment of the platoon penetration or platoon size, the road capacity gradually increased [29]. Considering the CAV advantages, such as the faster response speed and more compact and neat following distance, Gong et al. [30] developed a cooperative platoon control with constraint optimization to ensure both transient traffic smoothness and asymptotic stability of the mixed flow platoon. Lee et al. [17] proposed a novel traffic management strategy in automated driving environments, which can enhance both traffic safety and mobility performance by adjusting the driving aggressiveness of CAV operations. Regarding the mixed traffic flow as a multiclass traffic assignment problem, Wu et al. [31] showed the existence and uniqueness of link flow and path flow patterns at both user equilibrium and system optimum. Furthermore, this problem was formulated as a nonlinear complementarity problem which was solved to find optimal traffic management policies. Results of numerical examples for a real size network showed that management policies can decrease the gap between user equilibrium and system optimal to less than 1% [32].

To summarize, previous studies have affirmed the effectiveness of the vehicle platooning technology on improving the road capacity. From the perspective of macrolevel, existing research mainly focuses on the positive aspects of the CAV technology, while the negative effects of CAV platoons got less attention despite that they will block the HDV flow under mixed traffic environment. To this end, a mixed traffic flow model is proposed based on UE-SUE mixed equilibrium, which considers both the positive and negative sides of CAV platooning. On the positive side, considering the CAV advantage in information perception, CAV platoons are assumed to follow user equilibrium (UE) for route choice, while HDVs to follow stochastic user equilibrium (SUE). In addition, CAV platooning is presumed to improve the road capacity. On the negative side, the speed of CAV platoons should be slower than that of nonplatooning HDVs for safety issues. A long CAV platoon with a slow speed may impede HDVs to overtake and change lanes. The CAV platooning model is formulated as a nonlinear complementarity problem and solved by GAMS software. Different from existing studies, numerical results on the proposed model shows that, in congested conditions, the road network performance deteriorates at the beginning of the diffusion stage of CAV platooning. In other words, the more CAV platoons, the worse the network traffic performance, as the negative side of CAV platooning overwhelms its positive side. Only when the CAV market penetration rate reaches a threshold, the road network will improve with the increase of CAV platoons. Therefore, to alleviate the negative effects of CAV platoons, we further propose an optimal path platooning method for CAV, which takes the travel costs of both CAV platoons and HDVs into the objective function. Numerical results show that the proposed method can effectively reduce the disturbance caused by CAV platoons and improve the road network performance.

Table 1: Symbols and definitions.

Symbols	Definitions
N	The set of nodes
W	The set of origin-destination pairs
θ	The perception parameter
d_w	Traffic demand for OD pair w
μ_a	The congestion degree on road a
c_a	The road capacity
$\delta_{w,r}^a$	Link-route incidence
λ_P	Platooning disturbance parameter
v_P^a	Platooning flow on road a
t_P^a	Travel time of CAV platoon on road a
t_0^a	The CAV free-flow travel time on road a
e_P^a	The platoon driving speed
$\pi_{w,r}^P$	Travel cost of platooning vehicle on route r
$x_{w,r}^P$	Platooning flow for route r
P_w^r	The flow proportion of HDV on route r
$\mathcal{A}$	The set of links
y	CAV market penetration rate (MPR)
η	The speed ratio of CAV and HDV
R_w	The set of routes in OD pair w
L^a	The distance of the road a
C_w	The minimum travel cost of OD pair w
P_a	The overtaking probability of nonplatooning vehicle on road a
k_P	The CAV congestion discount rate
v_{NP}^a	Nonplatooning flow on road a
t_{NP}^a	Travel time of HDV with overtaking opportunity on road a
$t_{0,NP}^a$	The HDV free-flow travel time
e_{NP}^a	The overtaking speed of HDV
$\pi_{w,r}^{NP}$	Travel cost of nonplatooning vehicle on route r
$x_{w,r}^{NP}$	Nonplatooning flow for route r

The contributions of this study are summarized as follows:

(1) A mixed traffic flow model was developed for CAV platoons based on UE-SUE mixed equilibrium, to the best of our knowledge, which is the first macroscopic traffic model that considers both the positive and negative sides of CAV platooning.

(2) Numerical results conducted on a test road network show that the total network performance could be worse by the application of CAV platoons at the beginning stage, which indicates a need for optimizing the platooning path to promote wider CAV platooning applications.

(3) A CAV optimal path platooning method is proposed, which integrates the travel costs of both CAV platoons and HDVs into its objective function and formulated as a nonlinear complementarity problem. Numerical results show that it helps to reduce the platooning disturbance and improve the road network performance.

The rest of this paper is organized as follows. Section 2 provides necessary assumptions and definitions and models the mixed traffic of CAV platoons and HDVs as a nonlinear complementarity problem. Section 3 proposes a CAV optimal path platooning method based on the mixed equilibrium model. Then, in Section 4, numerical experiments are conducted and analyzed. Section 5 concludes this study and gives future work.

2. Mixed Equilibrium Model

With high level of automation and information perception, CAVs can not only improve the road capacity by driving in platoons but also find their best routes under the current traffic conditions. Due to the gap in information perception and other uncontrollable human factors, HDVs cannot drive automatically in platoons, and their driving routes are randomly distributed with the travel cost. To better understand the traffic impacts of CAV platooning, in this section a mixed equilibrium model is developed based on the UE-SUE flow patterns, where CAV platoons and HDVs are presumed to choose their routes following user equilibrium and stochastic user equilibrium, respectively.

2.1. Basic Assumptions and Symbol Definitions. The specific symbols and their definitions involved in this paper are listed in Table 1. However, the model imposes some assumptions listed as follows:

Assumption 1. CAV platooning can improve the road capacity. CAV platoons can significantly reduce the average intraplatoon headway through the effective multivehicle cooperative longitudinal and lateral control. Hence, multiple CAVs can drive like one single and long vehicle, which increases the maximum number of acceptable vehicles on the road. In other words, the traffic congestion attributed to CAVs should be smaller than that of HDVs driving alone. The congestion degree on the road a is described as the following equation:

$$\mu_a = \frac{v_{NP}^a + v_P^a / k_P}{c_a}, \forall a \in \mathscr{A}, \quad (1)$$

where v_P^a and v_{NP}^a are, respectively, the flow of platooning CAVs and nonplatooning HDVs on road a, $k_P > 1$ is the CAV congestion discount rate, and c_a is the road capacity.

Assumption 2. The driving speed of CAV platoons is lower than the average speed of nonplatooning HDVs on the same road. Considering the large equivalent inertia of CAV platoon, its safe driving speed will be lower than that of HDVs. According to the Bureau of Public Roads impedance function, the travel time of CAV platoons on the road a is as follows:

$$t_P^a = t_0^a \left(1 + \beta_a \mu_a^\kappa\right), \quad (2)$$

where $t_0^a = L^a / e_P^a$ is the CAV platooning free-flow travel time on road a, which is directly proportional to the distance of the road and inversely proportional to the platoon speed e_P^a. β and κ are impedance coefficients in the Bureau of Public Roads impedance function, which can be calibrated by the real world road traffic data. The travel time for HDVs with overtaking opportunity is $t_{NP}^a = t_{0,NP}^a (1 + \beta_a \mu_a^\kappa)$, where $t_{0,NP}^a = L^a / e_{NP}^a$ is the HDV free-flow travel time and e_{NP}^a is their overtaking speed. Considering the safety factor, the speed of CAV platoon will be lower than that of HDV to a certain extent, with $e_{NP}^a = e_P^a / \eta$ and $0 < \eta < 1$. Hence, the t_{NP}^a can be reformulated as follows:

$$t_{NP}^a = \eta t_0^a \left(1 + \beta_a \mu_a^\kappa\right). \quad (3)$$

Assumption 3. The driving of nonplatooning HDVs will be disturbed by the existence of CAV platoons. The greater amount of CAV platoon flow, the lower the overtaking chance for HDVs. The overtaking probability of HDVs can be described in detail as follows:

$$P_a = e^{-\lambda_P v_P^a / c_a}, \quad (4)$$

where λ_P is a parameter for the platooning disturbance. It is introduced as the weighting parameter to describe the CAV platoon's blocking effect, which is interpreted as the overtaking probability for nonplatooning HDVs to bypass CAV platoons. The overtaking probability is normalized within the range [0, 1] by the exponential function, and monotonically decreases with the increasing λ_P. As mentioned previously, the travel time of overtaking HDVs is t_{NP}^a, which is smaller than that of CAV platoons. But for HDVs without overtaking chance, their travel time is the same as that of CAV platoon, equals to t_P^a. Therefore, the average travel time of HDVs on road a can be calculated as follows:

$$\overline{t}_{NP}^a = P_a t_{NP}^a + \left(1 - P_a\right) t_P^a. \quad (5)$$

2.2. UE-SUE Mixed Traffic Assignment. The UE-SUE mixed traffic assignment is used to model the mixed traffic flow of nonplatooning HDVs and CAV platoons. Due to the human drivers' diversified perception levels, their route choices exhibit randomness, which will adjust with the change of external conditions, and finally, reach to the stochastic user equilibrium (SUE). SUE equilibrium state is attained if the perceived travel time of all alternative routes of the same OD pair is equal. Based on the logit model, for an OD pair w, the probability of HDVs choosing the route r satisfies the following conditions:

$$P_w^r = \frac{e^{-\theta \pi_{w,r}^{NP}}}{\sum_{k \in R_w} e^{-\theta \pi_{w,k}^{NP}}}, \forall r \in R_w; \forall w \in W, \quad (6)$$

where $\pi_{w,r}^{NP} = \sum_{a \in A} \delta_{w,r}^a \overline{t}_{NP}^a$ is the HDV travel cost for the route r and θ is the perception parameter. $\delta_{w,r}^a$ is the link-route incidence, which equals 1 if link a belongs to route r and 0 otherwise. Therefore, the HDV flow for route r is as follows:

$$x_{w,r}^{NP} = P_w^r d_w (1 - y), \quad (7)$$

where y is the CAV market penetration rate.

CAV has better information perception ability, so when CAV platoons choose their route, they aim at minimizing their own travel cost, following the Wardrop conditions. Therefore, the traffic flow of CAV platoons will eventually reach their user equilibrium as follows:

$$\begin{cases} x_{w,r}^{P} > 0, \pi_{w,r}^{P} = C_w, \\ x_{w,r}^{P} = 0, \pi_{w,r}^{P} > C_w, \end{cases} \tag{8}$$

where $\pi_{w,r}^{P} = \sum_{a\in A}\delta_{w,r}^{a} t_{P}^{a}$ is the CAV platoon travel cost for the route r and C_w represents the minimum travel cost of OD pair w. $x_{w,r}^{P}$ is the traffic flow of CAV platoons along the route r, satisfying the following constraint:

$$\sum_{r\in R_w} x_{w,r}^{P} = d_w y, \tag{9}$$

where d_w is denoted as the traffic demand for OD pair w.

Finally, according to the flow constraints of route r and road a, we have,

$$\begin{cases} v_{NP}^{a} = \sum_{w\in W}\sum_{r\in R_w} \delta_{w,r}^{a} x_{w,r}^{NP}, \\ v_{P}^{a} = \sum_{w\in W}\sum_{r\in R_w} \delta_{w,r}^{a} x_{w,r}^{P}. \end{cases} \tag{10}$$

2.3. The Mixed NCP Formulation. In order to model the previous problem in a more concise way, it is reformulated into a nonlinear complementarity problem (NCP), which can thus be solved conveniently by software like GAMS.

The NCP problem is equivalent to the variational inequality problem. To solve it, a vector x^* that strictly satisfies the following conditions should be found:

$$\begin{cases} F(x)^{T} x = 0, \\ F(x) \geq 0, \\ x \geq 0, \end{cases} \tag{11}$$

where x is a nonnegative vector and $F(x)$ is a given vector function. These formulas can also be more compactly expressed as: $0 \leq x \perp F(x) \geq 0$, where symbol " $\perp$ " represents the projection of x over $F(x)$.

For CAV platoons following the UE principle, their traffic flow equilibrium conditions (8) can be rewritten into the complementarity format as follows:

$$0 \leq x_{w,r}^{P} \perp \left\{\pi_{w,r}^{P} - C_w\right\} \geq 0. \tag{12}$$

As for the route flow constraint of CAV platoons, given that the minimum travel cost C_w is always nonnegative, constraint (9) can be associated with C_w and reformulated as follows:

$$0 \leq C_w \perp \left\{\sum_{r\in R_w} x_{w,r}^{P} - d_w y\right\} \geq 0. \tag{13}$$

For HDVs following the SUE principle, as $P_w^r \geq 0$ always holds, the logit constraint condition (6) can be reformulated as follows:

$$0 \leq P_w^r \perp \left\{P_w^r - \frac{e^{-\theta\pi_{w,r}^{NP}}}{\sum_{k\in R_w} e^{-\theta\pi_{w,k}^{NP}}}\right\} \geq 0. \tag{14}$$

Moreover, based on the definition of the HDV route flow probability and its nonnegativity, we can obtain the following:

$$0 \leq x_{w,r}^{NP} \perp \left\{x_{w,r}^{NP} - P_w^r d_w (1-y)\right\} \geq 0. \tag{15}$$

With (12)–(15), now we can establish a NCP formulation of the UE-SUE model: [UE-SUE-NCP]

$$\begin{cases} 0 \leq x_{w,r}^{P} \perp \left\{\pi_{w,r}^{P} - C_w\right\} \geq 0, \\ 0 \leq C_w \perp \left\{\sum_{r\in R_w} x_{w,r}^{P} - d_w y\right\} \geq 0, \\ 0 \leq P_w^r \perp \left\{P_w^r - \frac{e^{-\theta\pi_{w,r}^{NP}}}{\sum_{k\in R_w} e^{-\theta\pi_{w,k}^{NP}}}\right\} \geq 0, \\ 0 \leq x_{w,r}^{NP} \perp \left\{x_{w,r}^{NP} - P_w^r d_w (1-y)\right\} \geq 0. \end{cases} \tag{16}$$

It should be noted that, for brevity, definitional constrains (1)–(5) are not reformulated into the NCP format. But they are also considered as parts of the UE-SUE-NCP model, and their NCP format can be easily obtained just like equations (14) and (15).

3. CAV Optimal Path Platooning

To mitigate the traffic disturbance caused by CAV platoons, a CAV platooning method is proposed with optimized path planning based on the previous UE-SUE-NCP model. It takes full advantage of the CAV benefits, such as better information interaction ability and greater willingness to obey the dispatch commands from traffic managers. To consider both the travel cost of CAV platoons and non-platooning HDVs, the traffic dispatching center takes the total travel cost of the road network as the objective function when calculating the travel path for each CAV platoon, formulating the following CAV optimal path platooning problem: [CAV-OPP]

$$\min_{\mathbf{x}_P} Z(\mathbf{x}_P) = \sum_{a\in\mathscr{A}} v_P^a t_P^a + v_{NP}^a \overline{t}_{NP}^a. \tag{17}$$

Subject to

$$\sum_{r\in R_w} x_{w,r}^{P} = \mathrm{d}_w y, \tag{18}$$

$$x_{w,r}^{P} \geq 0. \tag{19}$$

In order to find the optimal solution of the previous constrained optimization problem, two sets of Lagrangian multipliers λ_w and $\tau_{w,r}$ are associated with the constraints

(18) and (19), respectively. However, the Lagrangian function is then formulated as follows:

$$L(\mathbf{x}_P, \boldsymbol{\lambda}, \boldsymbol{\tau}) \overset{\text{def}}{=} Z(\mathbf{x}_P) - \sum_{w \in W} \lambda_w \left(\sum_{r \in R_w} x_{w,r}^P - d_w y \right) - \sum_{r \in R_w} \tau_{w,r} x_{w,r}^P. \quad (20)$$

The derivative of the Lagrangian function can be expressed as follows:

$$\nabla_x L(\mathbf{x}_P, \boldsymbol{\lambda}, \boldsymbol{\tau}) = \frac{\partial Z(\mathbf{x}_P)}{\partial x_{w,r}^P} - \lambda_w - \tau_{w,r} = \sum_{a \in A} \delta_{w,r}^a \left(t_P^a + v_P^a t_P^{a\prime} + v_{NP}^a \bar{t}_{NP}^{a\prime} \right) - \lambda_w - \tau_{w,r}, \quad (21)$$

where

$$t_P^{a\prime} = \frac{\partial t_P^a}{\partial v_P^a} = \frac{\kappa}{k_p c_a} t_0^a \beta_a \mu_a^{\kappa - 1}, \quad (22)$$

$$\bar{t}_{NP}^{a\prime} = \frac{\partial \bar{t}_{NP}^a}{\partial v_P^a} = \frac{\lambda_P}{c_a} P_a \left(P_a - \eta P_a \right) t_P^a + \left(1 - P_a + \eta P_a \right) t_P^{a\prime} \quad (23)$$

To solve the CAV-OPP problem, the first-order necessary conditions of constrained optimization problem are introduced as follows:

$$\sum_{a \in A} \delta_{w,r}^a \left(t_P^a + v_P^a t_P^{a\prime} + v_{NP}^a \bar{t}_{NP}^{a\prime} \right) - \lambda_w - \tau_{w,r} = 0, \quad (24)$$

$$\tau_{w,r} x_{w,r}^P = 0, \quad (25)$$

$$\tau_{w,r} \geq 0, \quad (26)$$

$$\lambda_w \left(\sum_{r \in R_w} x_{w,r}^P - d_w y \right) = 0, \quad (27)$$

$$\lambda_w \geq 0. \quad (28)$$

According to constraint (24), $\tau_{w,r} = \sum_{a \in A} \delta_{w,r}^a (t_P^a + v_P^a t_P^{a\prime} + v_{NP}^a \bar{t}_{NP}^{a\prime}) - \lambda_w$. Substituting it into constraints (25) and (26), and combining with constraint condition (19), we can deduce the following NCP formula:

$$0 \leq x_{w,r}^P \perp \left\{ \sum_{a \in A} \delta_{w,r}^a \left(t_P^a + v_P^a t_P^{a\prime} + v_{NP}^a \bar{t}_{NP}^{a\prime} \right) - \lambda_w \right\} \geq 0. \quad (29)$$

Then, constraints (18), (27) and (28) can be further rewritten as the following complementarity format:

$$0 \leq \lambda_w \perp \left\{ \sum_{r \in R_w} x_{w,r}^P - d_w y \right\} \geq 0. \quad (30)$$

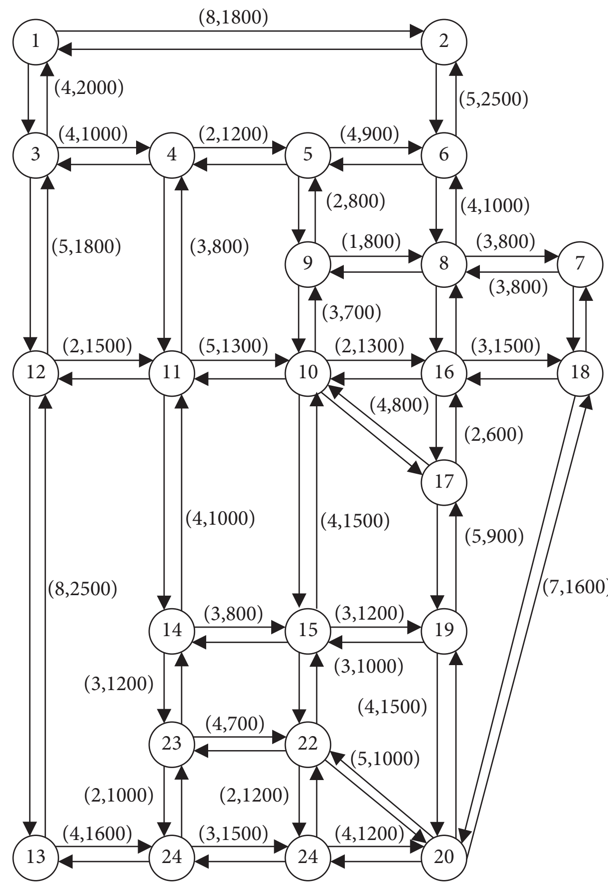

Figure 1: Sioux-Falls network.

On the basis of the UE-SUE-NCP model shown in constraint (16), combined with NCP constraints (14), (15), (29) and (30), the NCP format of CAV-OPP problem is obtained as: [CAV-OPP-NCP]

$$\begin{cases} 0 \leq x_{w,r}^P \perp \left\{ \sum_{a \in A} \delta_{w,r}^a \left(t_P^a + v_P^a t_P^{a\prime} + v_{NP}^a \bar{t}_{NP}^{a\prime} \right) - \lambda_w \right\} \geq 0, \\ 0 \leq \lambda_w \perp \left\{ \sum_{r \in R_w} x_{w,r}^P - d_w y \right\} \geq 0, \\ 0 \leq P_w^r \perp \left\{ P_w^r - \dfrac{e^{-\theta \pi_{w,r}^{NP}}}{\sum_{k \in R_w} e^{-\theta \pi_{w,k}^{NP}}} \right\} \geq 0, \\ 0 \leq x_{w,r}^{NP} \perp \left\{ x_{w,r}^{NP} - P_w^r d_w (1 - y) \right\} \geq 0. \end{cases} \quad (31)$$

4. Numerical Analyses

To examine the influence of CAV platoons under mixed traffic environment and further verify the effectiveness of the proposed optimal path platooning method, numerical

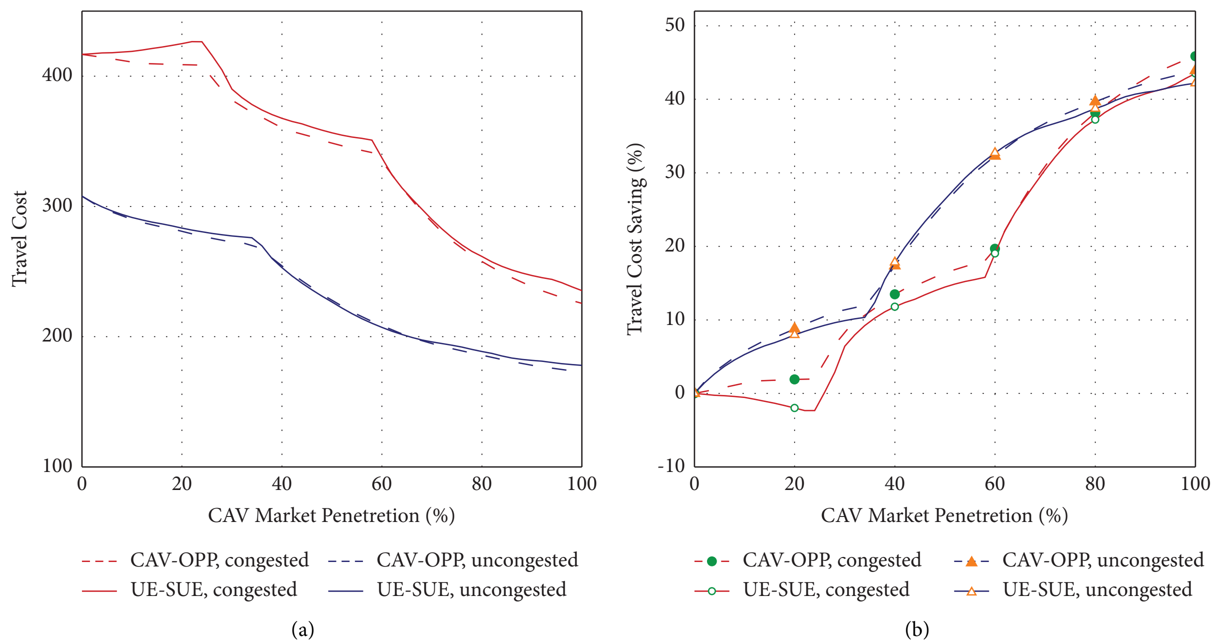

Figure 2: Comparison of two platooning strategies with various CAV market penetration rates. (a) Travel cost. (b) Travel cost saving.

experiments are conducted on the classic Sioux- Falls network. All numerical examples are implemented in a PC with 8-core 3.4 GHz CPU and 32 GB RAM.

4.1. Model Parameter Setting. In reality, the demand for a given OD pair is not static, and the traffic flow is variable in different travel periods. To simplify the analysis, the traffic conditions are divided into congestion and noncongestion cases. Both cases are with the same sets of OD pairs and model parameters, while the total traffic demand of the uncongested case is 20 percentage less than that of the congested one.

The Sioux-Falls network includes 24 nodes, 76 links, and the links between the two nodes are two-way roads. Its basic information is shown in Figure 1. The road section is annotated with (α_a, c_a), where $\alpha_a = \eta t_0^a$ is the free travel time of overtaking HDVs, and c_a is the road capacity. The default model values are set as $\lambda_P = 0.3$, $k_P = 3$ and $\eta = 0.85$.

4.2. Impact of CAV Market Penetration Rate. To examine the influence of CAV platooning under mixed CAV-HDV traffic environment, numerical analyses are conducted with increasing CAV market penetration rate for both congested and uncongested cases, while other parameters remain the same. The main results are shown in Figure 2.

For the uncongested case, not surprisingly, the network performance improves with the growing amount of penetration, as the CAV platooning improves the utilization efficiency of road capacity. However, for the congested case, it is not always beneficial to impose the platooning technology. On the contrary, the network performance deteriorates at the early stage of the penetration process. As illustrated in Figure 2(a), the total travel cost increases with the CAV penetration rate, if it is smaller than 25%. When market penetration rate grows up to 20%, the network performance is 1.98% worse off, as shown in Table 2. This is attributable to the negative effects of CAV platooning, such as the heterogeneous vehicle platoon and the bottleneck effects. It is remarkable that these negative effects are exacerbated under the congested case.

To alleviate these negative effects caused by CAV platoons, we propose an optimal path platooning method, namely, CAV-OPP. Numerical results show the superiority of CAV-OPP, which outperforms UE-SUE for all penetration settings. By means of CAV-OPP, the network performance always improves with the increasing amount of penetration, under both congested and uncongested cases. The improvement is remarkable for the congested case with small penetration. When penetration equals to 20 percent, CAV-OPP saves 1.91% travel cost, while oppositely UE-SUE incurs 1.98% loss. This indicates that CAV-OPP will help to promote the CAV platooning technology especially at the early stage.

Interestingly, there are two inflection points in Figure 2. The first inflection point lies in the HDV-dominating scenario, where the CAV market penetretion rate is smaller than 50%. The travel cost first increases and then decreases after the inflection point, which has been well discussed at the beginning of this subsection. Moreover, there is also a inflection point in the CAV-dominating scenario. When the CAV market penetretion rate is larger than 50%, the travel cost first goes down smoothly and then drops off sharply after the second inflection point. The reason may be the "economies of scale" effect of CAV technology, as the larger the scale of CAVs, the more the cost savings.

Table 2: Travel cost saving rate (%).

Scenarios	Penetration					
	0%	20%	40%	60%	80%	100%
CAV-OPP, congested	0	1.91	13.47	19.67	38.17	45.86
UE-SUE, congested	0	−1.98	11.79	19.04	37.23	43.51
CAV-OPP, uncongested	0	8.78	17.36	32.28	39.68	43.90
UE-SUE, uncongested	0	7.96	17.82	32.72	38.72	42.19
Average	0	4.17	15.11	25.93	38.45	43.87

4.3. Parameter Analysis. To give a more comprehensive examination of the proposed model and method, some important parameters involving the traffic demand, disturbance, congestion reduction, and safety speed of the CAV platoons are further analyzed as follows. The parameter analysis is conducted under three typical CAV penetration rate settings, the HDV-dominating case with $y = 0.1$, the CAV-dominating case with $y = 0.9$, and the equilibrium case with $y = 0.5$.

4.3.1. Impacts of the Traffic Demand. Due to the influence of uncertain factors such as travel time, destination, and weather, the traffic demand will fluctuate continuously in a real-world transportation environment. To further verify the applicability of the proposed method, numerical analyses are conducted under various travel demand level. As shown in Figure 3, the travel costs of all settings are generally increasing with the growth of the relative traffic demand level. It is worth to note that, when the relative traffic demand exceeds a certain level, the UE-SUE travel cost of the equilibrium case (with $y = 0.5$) will be worse than that of the HDV-dominating case (with $y = 0.1$). This is due to the negative effect of CAV platoons, as analyzed before in Section 4.2. CAV-OPP is helpful to reduce the travel costs under all cases. Especially, under the same travel demand, CAV-OPP always helps achieving a lower travel cost for a higher CAV penetration rate.

4.3.2. Impacts of the CAV Platooning Disturbance. As mentioned in assumption 3, the existence of CAV platoons will impede HDVs to overtake and thus affect the performance of the traffic networks. To validate it, we have investigated the effects of CAV platoon disturbance parameter λ_p which represents the degree of negative impact of CAV platoons. The results in Figure 4(a) show that the models are not very sensitive to this parameter, as the travel cost of the road network is only slightly increased with the growing disturbance degree. It also can be seen in Figure 4(a) that the performance of the proposed CAV-OPP method is always better than that of UE-SUE.

4.3.3. Impacts of CAV Congestion Discount Rate. The CAV congestion discount rate k_p, as mentioned in assumption 1, is related to the beneficial aspect of CAV platooning that multiple CAVs can cooperatively drive like a single car and incur less congestion. The influence of this parameter is illustrated in Figure 4(b). For the HDV-dominating case (with

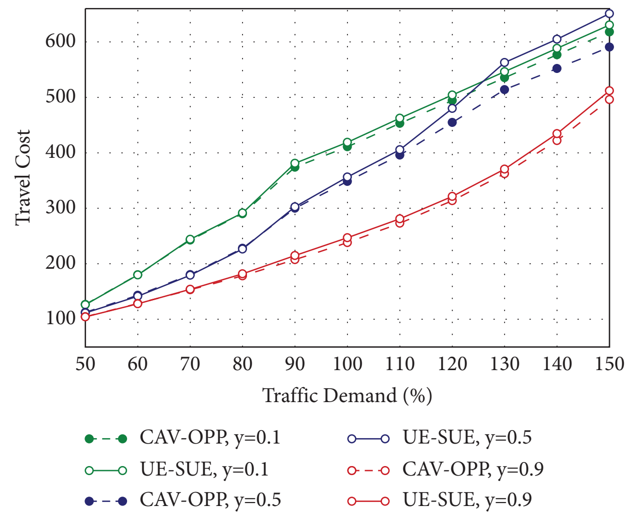

Figure 3: Comparison of two platooning strategies under different traffic demands.

$y = 0.1$), the travel cost is not sensitive to this parameter. However, for the equilibrium case (with $y = 0.5$) and CAV-dominating case (with $y = 0.9$), the parameter k_p plays a more important role. With the increase of k_p, the overall network performance first decreases and then increases. When the congestion discount rate is close to 1, the platooning CAVs act just as the normal nonplatooning HDVs in terms of the congestion contribution, but their long platooning length and poor flexibility will impede the overtaking of nonplatooning HDVs. This reasonably explains why the network performance will decline at the initial stage, regardless of whether CAV platoons follow CAV-OPP or UE-SUE. Later, when k_p is larger than 1.5, the network performance is improved rapidly. This is because the benefits of CAV platooning overwhelm its negative defects.

4.3.4. Impacts of CAV Platooning Speed. As mentioned in assumption 1, the CAV platooning speed is always lower than that of more flexible nonplatooning HDVs for safety stakes. The speed ratio η describes the relative speed between CAV platoons and the overtaking HDVs, as $\eta = e_P^a / e_{NP}^a$. Figure 4(c) shows the influence of the platooning speed on the total network performance, with speed ratio η ranging from 0.5 to 1, while the free-flow speed of overtaking HDVs is fixed. It is shown that the closer the speed of the two types of vehicles is, the better the network performance will be, since CAV platoons drive as fast as HDVs. Moreover, the road network performs better with the help of CAV-OPP. It is worth noting that the improvement is more significant when the speed of CAV platoons and overtaking HDVs gets closer. The reason behind this may be that the slower CAV platooning speed will make HDVs easier to choose their routes to avoid blocking CAV platoons. For the HDV-dominating case, an abnormality is observed at the end of the curve such that the travel cost of UE-SUE is lower than CAV-OPP. This may happen because the CAV platoons with UE mode will tend to travel in the shortest route, while the

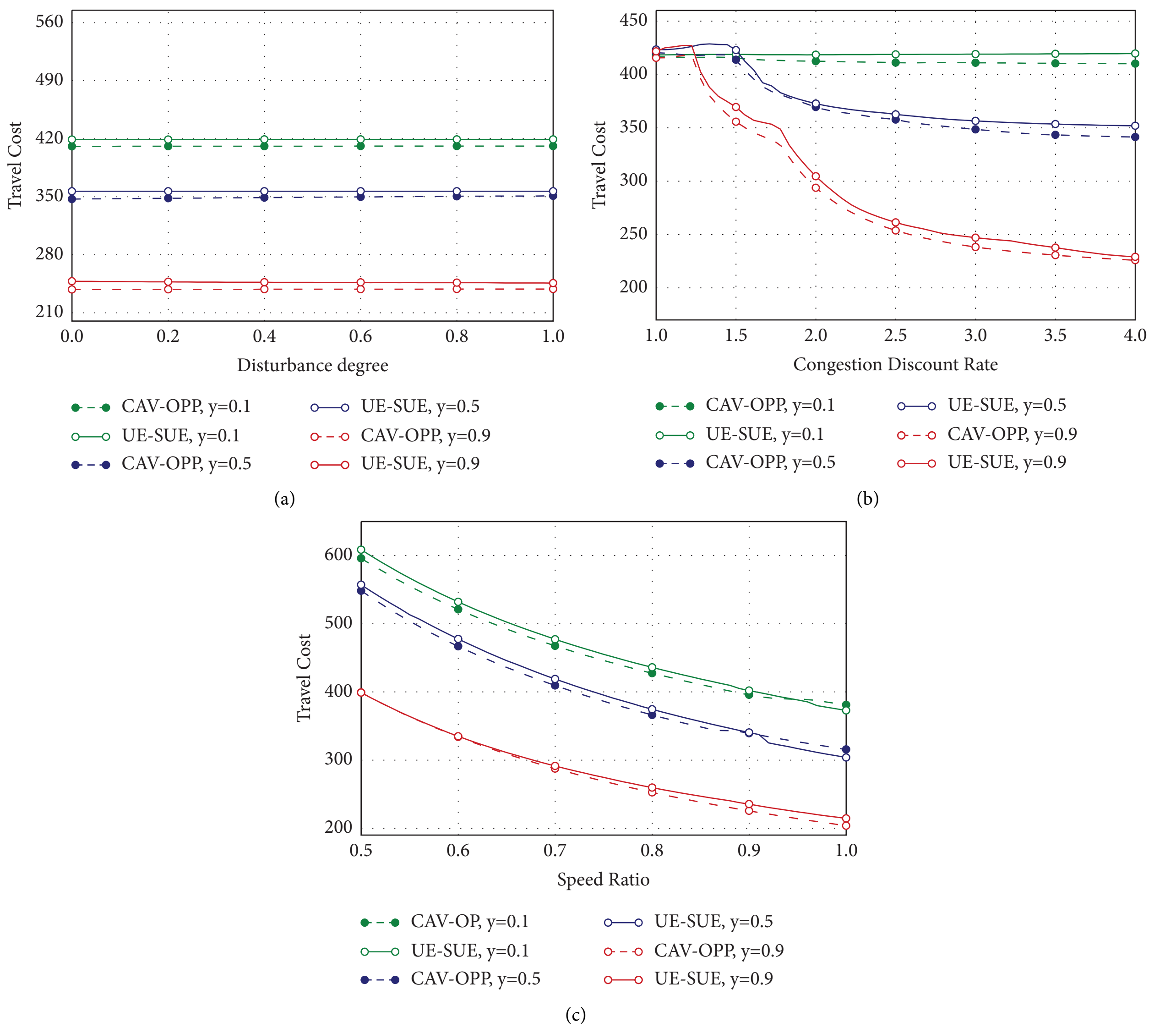

Figure 4: Parameter analysis with different CAV penetration rates. (a) Disturbance degree. (b) Congestion discount rate. (c) Speed ratio.

similar travel speeds may suppress HDVs' overtaking attempts, and thus cause less congestion.

5. Conclusions

A UE-SUE mixed equilibrium model is set up to investigate the impact of CAV platoons driving into the heterogenous traffic environment. Based on the mixed equilibrium model, a CAV optimal path platooning method is then proposed to alleviate their negative defects. Numerical results are conducted on the Sioux-Falls network, and the following conclusions can be drawn:

(1) The travel costs always decrease in the road network with the increase of CAV platooning traffic under light traffic. In the contrast, for heavy traffic, the road network may deteriorate at the beginning stage of the CAV diffusion, in which the more CAV platooning traffic, the worse the network traffic performance.

(2) The proposed CAV optimal path platooning method will significantly improve the road network performance in a heavy traffic flow when the CAV penetration rate is low. Since the negative defects of CAV platoons can be effectively mitigated by reducing traffic disturbance to other HDVs, which will help to promote the CAV platooning technology especially for its application in the early period.

This study mainly focuses on the vehicle platooning and route choice problem at the macrolevel. In future work, microspecific strategies such as the car-following control and lane-changing rules will be conjunctively considered along with the proposed optimal path platooning method.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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